Rangeland Ecology & Management xxx (2018) xxx–xxx

Contents lists available at ScienceDirect

Rangeland Ecology & Management

journal homepage: http://www.elsevier.com/locate/rama

Appropriate Sample Sizes for Monitoring Burned Pastures in Sagebrush Steppe: How Many Plots are Enough, and Can One Size Fit All?☆,☆☆

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ARTICLE INFO

Article history:
Received 8 September 2017
Received in revised form 14 May 2018
Accepted 14 May 2018
Available online xxxx

Key Words:
adaptive management
power analysis
relative standard error
rangeland
sampling
wildfire

ABSTRACT

Statistically defensible information on vegetation conditions is needed to guide rangeland management decisions following disturbances such as wildfire, often for heterogeneous pastures. Here we evaluate sampling effort needed to achieve a robust statistical threshold using >2 000 plots sampled on the 2015 Soda Fire that burned across 75 pastures and 113 000 ha in Idaho and Oregon. We predicted that the number of plots required to generate a threshold of standard error/mean ≤ 0.2 (TSR, threshold sampling requirement) for plant cover within pasture units would vary between sampling methods (rapid ocular versus grid-point intercept) and among plot sizes (1, 6, or 531 m^2), as well as relative to topography, elevation, pasture size, spatial complexity of soils, vegetation treatments (herbicide or seeding), and dominance by exotic annual or perennial grasses. Sampling was adequate for determining exotic annual and perennial grass cover in about half of the pastures. A tradeoff in number versus size of plots sampled was apparent, whereby TSR was attainable with less area searched using smaller plot sizes (1 compared with 531 m^2) in spite of less variability between larger plots. TSR for both grass types decreased as their dominance increased (0.5–1.5 plots per % cover increment). TSR decreased for perennial grass but increased for exotic annual grass with higher elevations. TSR increased with standard deviation of elevation for perennial grass sampled with grid-point intercept. Sampling effort could be more reliably predicted from landscape variables for the grid-point compared with the ocular sampling method. These findings suggest that adjusting the number and size of sample plots within a pasture or burn area using easily determined landscape variables could increase monitoring efficiency and effectiveness.

Introduction

The increased use of adaptive management to bolster ecosystem resistance and resilience following disturbance is leading to increased demand for precise and accurate monitoring data (Legg and Nagy, 2006). Rangeland monitoring, however, is often complicated by the heterogeneous characteristics of large management units, such as allotments and pastures. Following wildfires, monitoring plans must be quickly devised to enable timely, defensible management decisions, especially regarding land treatments like seeding or herbicide application. Rangeland monitoring programs are evolving from convenience-oriented, qualitative sampling toward quantitative methods (e.g., line-point intercept) and probabilistic designs that improve prospects for statistical inference. For example, the Bureau of Land Management's (BLM) Assessment Inventory and Monitoring (AIM) program[2] has adopted standardized methods and sampling designs for detecting trends in rangelands across multiple spatial scales (Toevs et al., 2011).

Despite advances in rangeland monitoring, evaluation of the statistical adequacy of monitoring methods and designs is rare and few studies have addressed this important issue. Statistical assessments of sampling adequacy require datasets with sufficient oversampling, especially that span environmental and topographic gradients (Legg and Nagy, 2006). The need for such analyses is acute in sagebrush steppe ecosystems, where post-fire monitoring is routinely conducted on large burned areas that span multiple management units (i.e., pastures) and heterogeneous landscapes (Pilliod et al., 2017). Sampling-effort studies in sagebrush steppe have thus far focused on inferences possible with oversampling of relatively small (1–2 ha) areas, with a focus on grid-point intercept techniques in the field (Inouye, 2002; Pilliod and Arkle, 2013). Information is needed on how these techniques could scale to

☆ Support: Bureau of Land Management, Great Basin Landscape Conservation Cooperative Program, and the Joint Fire Sciences Program.
☆☆ Disclaimer: Any use of trade, product or firm names is for descriptive purposes only and does not imply endorsement by the US Government.
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[2] http://aim.landscapetoolbox.org/

https://doi.org/10.1016/j.rama.2018.05.003
1550-7424/Published by Elsevier Inc. on behalf of The Society for Range Management.

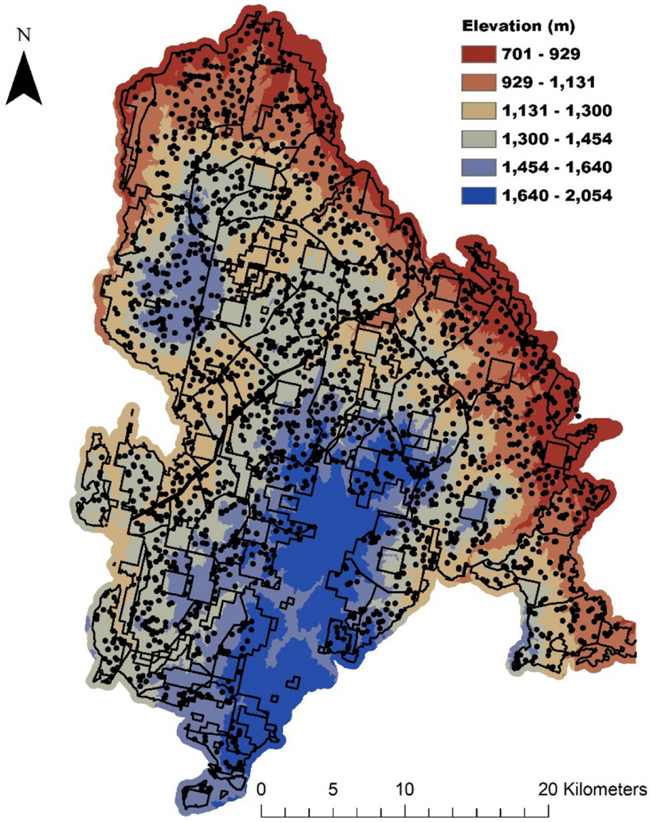

Figure 1. Perimeter and pasture boundaries of the Soda Fire (solid black lines). The black and round symbols show the location of sampled plots. Elevation (color scale) ranges from 701 to 2 054 m (US Geological Survey's Digital Elevation Model, 30 m pixels).

large-landscape applications, in which sampling must usually occur in a short, phenologically constrained period.

We recently initiated an intensive monitoring effort of >2 000 plots over 113 000 ha of sagebrush steppe on the 2015 Soda Fire in the Owyhee Mountains of southwestern Idaho and southeastern Oregon (Fig. 1), which had high variation in topography, management units, and post-fire treatments. This physical, ecological, and jurisdictional variation provides an opportunity for assessing sample size considerations. In some portions of the landscape, the quantity of plots saturated the number needed to minimize variance in mean estimation, allowing us a rare opportunity to analyze threshold sampling requirements (TSR) at the landscape level. TSR is determined here as the number of plots required to decrease the relative standard error (RSE) to < 0.2 (standard error/mean). This criteria is used as a demonstration of a technique to determine sampling needs (McCune and Grace, 2002), but in practice can be set at any level appropriate to a specific monitoring project. The objective of this paper was to provide a basis for estimating sampling needs in the design of post-fire monitoring protocols, specifically in pastures, which usually encompass a more heterogeneous area than treatment boundaries and therefore provide an intensive sampling scenario. We address the following questions for cover of exotic annual and perennial grass, as they typically dominate recently burned sagebrush steppe (Chambers et al., 2014):

- Of those pastures that meet < 0.2 RSE criteria, how does the number of plots per pasture needed to attain that criteria compare among different plot sizes (1 or 531 m^2) measured with rapid ocular estimation, and does this differ for 6 m^2 plots measured using grid-point methodology intercept? Ocular estimation was selected for its traditional importance and digital-imagery grid-point intercept because it is rapid and archivable. Furthermore, Pilliod and Arkle (2013) demonstrated that grid-point intercept and line-point intercept produced similar cover estimates.
- How do pasture size and the mean values or variability in physical attributes (elevation, slope, soils), climate (precipitation, heat load), functional group dominance, and post-fire herbicide or drill treatments within pastures relate to TSR?

We predicted TSR would increase with smaller plot sizes and physiological or biological heterogeneity.

Methods

Study Area

The Soda Wildfire burned at high severity through salt desert, big sagebrush (*A. tridentata*), and low sagebrush (*A. arbuscula*) communities in various pre-fire conditions. Herbicide spraying (Imazapic 99 g a.i. ha^{-1}), aerial seeding of grasses, forbs, and shrubs using aircraft, and rangeland drill seeding of grasses were conducted by the BLM prior to our sampling (Table 1). Cattle were excluded following the fire through the time of our sampling.

Sampling Design and Methods

Coordinates for plot locations were generated using a stratified-random method at a density of 1 plot per 54.5 ha or denser (Fig. 1). Plots were moved if they overlaid roads, had ≥ 20% cattle trail area within a 18 m radius, or if they fell within 0.40 km of water troughs or ponds. We used two spatially nested methods to quantify percent plant cover at the same points: 1) rapid ocular field estimation (at 5% cover resolution up to 40%, 10% resolution above 40%) made without grid or line guidance for both a 1 m^2 square quadrat and a 531 m^2 (13-m radius circle) area, and 2) a grid-point intercept measurement on 6 m^2 rectangular aerial photographs captured from nadir at 2-m height (with Nikon Coolpix AW130, 16 megapixel) using Samplepoint software (v 1.43, 100 points/image, Booth et al., 2006; Pilliod and Arkle, 2013). Smaller plot areas occurred within the larger plots, on or near plot center.

Sampling occurred between April and October 2016, commencing approximately 8 months after the fire was declared contained. Most pastures were sampled within a period of several weeks to a month. Mean monthly temperatures measured at three USGS weather stations in the western section of the fire (between 1 264 m and 1 279 m in elevation) ranged from a low of –1°C in December 2015 to a high of 26°C in July 2016. Total precipitation for water year 2016 measured at the Idaho Department of Transportation weather station in the western section of the fire at 1 264 m was approximately 305 mm. Mean annual precipitation ranges from 232 to 550 mm and mean annual temperature ranges from 6.8°C to 10.8°C across the site (800 m^2 pixel PRISM data; 1950–2014; PRISM Climate Group, 2018).

Landscape Variables

We calculated the mean, standard deviation, and range of precipitation, elevation, slope, and heat load across pixels in each pasture. Climate data were obtained from PRISM (PRISM Climate Group, 2018) and elevation from US Geological Survey Digital Elevation Models (10 m pixels). Heat load is an index ranging from 0 to 1 and is based on topographic effects on solar gain (McCune and Keon, 2002). We also considered pasture size (obtained from BLM), plant functional group cover, diversity of soils, and post-fire treatments (herbicide or drill seeding). Spatial variability (i.e., diversity) in soils was represented by the sum of the areal portions of each soil mapping unit in each pasture (sum of p_i; from SSURGO, websoilsurvey.sc.egov.usda.gov) multiplied by ln (p_i), which is similar to the Shannon-Wiener diversity index. We

Table 1
Summary of seeding treatments conducted on the Soda Fire by the Bureau of Land Management during the fall and winter of 2015 to 2016. Under "seeding treatment" the seed delivery style is first listed ("drill" refers to rangeland drill seeding, and "aerial" refers to aerial broadcast seeding), then the plant functional group type (grass, shrub, or forb), and then whether species seeded were native or introduced. All shrubs seeded were native, and forbs included along with shrubs were either native or introduced.

Seeding treatment	Species	Rate (bulk kg · ha^{-1})	Ha
Drill, grass – Native	*Elymus wawaweiensis, Pseudoroegneria spicata, Poa secunda, Elymus lanceolatus*	12.3	874
Drill, grass – Introduced	*Agropyron cristatum, Agropyron fragile, Elymus lanceolatus*	13.0	6 142
Aerial, grass – Native	*Pseudoroegneria spicata, Elymus lanceolatus, Poa secunda*	13.3	7 289
Aerial, grass – Native	*Pseudoroegneria spicata, Poa secunda, Festuca idahoensis*	13.6	5 197
Aerial, grass – Native/Introduced	*Agropyron fragile, Elymus wawaweiensis, Pseudoroegneria spicata, Poa secunda*	13.8	7 482
Aerial, grass – Native/Introduced	*Agropyron fragile, Poa secunda, Elymus elymoides*	15.7	4 416
Aerial, grass – Native/Introduced	*^{x}Triticosecale, Leymus cinereus, Elymus lanceolatus*	20.7	545
Aerial, Shrub – Native	*Artemisia arbuscula*	0.9	7 549
Aerial, Shrub/Forb	*Medicago sativa, Sanguisorba minor, Achillea millefolium, Artemisia tridentata ssp. wyomingensis*	3.5–6.4	56 195
Aerial, Shrub/Forb	*Medicago sativa, Sanguisorba minor, Achillea millefolium, Artemisia tridentata ssp. tridentata*	3.4	6 839
Aerial, Forb – Native	*Penstemon eatonii, Penstemon acuminatus, Sphaeralcea grossulariifolia, Sphaeralcea munroana, Crepis occidentalis, Balsamorhiza sagittata, Astragulus filipes, Lomatium triternatum, Malacothrix glabrata*	0.9	2 886

evaluated spatial heterogeneity attributable to whether patches did or did not receive post-fire herbicide applications. We did not address aerial grass seeding treatments because virtually no grass seedlings were observed in these areas (outside of drill rows) in the first year. Drill or herbicide heterogeneity was represented as the proportion of area treated within each pasture, and we transformed this proportion so that an equal blend (of treated: untreated) was the greatest value on a scale of 0 to 0.5 (i.e., all proportions > 0.5 were subtracted from 1). Dominance of plant cover was represented as the mean percent cover of the functional group.

Data Analysis

We first calculated RSE for each plant functional group and plot size by sampling method for all 75 pastures, then identified those pastures for which plots collectively had RSE ≤ 0.2 and could therefore be used to determine how many fewer plots could have been sampled to meet TSR. Next, relationships of TSR and environmental parameters were explored.

TSR was determined using 1 000 Monte Carlo simulations to draw progressively larger sample populations, starting with 1 plot/pasture and incrementing to the total number of plots sampled in a given pasture. We did this for each functional group (exotic annual grass or perennial grass) and sampling method (1 m^2 or 531 m^2 rapid ocular plots and 6 m^2 grid-point intercept plots). We then identified the number of plots aligning with 0.2 RSE (with 95% confidence, i.e., the 950th value of 1 000 iterations of RSE). Significance of differences in TSR among the three different plot sizes and between the sampling methods (Question 1) was determined with analysis of variance (ANOVA) followed by Tukey's test.

To assess the relative importance of all landscape variables to TSR of each sampling method and vegetation type (Question 2) we used the random-forests method in the R package VSURF to select topography and environmental variables that best explained TSR (Genuer et al., 2015). We then ran multiple linear regressions on TSR using the topographic variables selected by the VSURF analysis. All plot size, method, and functional group combinations were considered separately.

Results

Plot Size and Sampling Method Effects

The number of plots sampled per pasture met or exceeded TSR in more pastures for the 531 compared with 1-m^2 plots (43 versus 18 pastures for exotic annual grass, and 52 versus 38 pastures for perennial grass, respectively, not shown). Between 10 and 15 additional plots/pasture were needed to meet TSR for the 1-m^2 compared with 531-m^2 plots ($F = 8.0$, $P < 0.001$ and $F = 12.7$, $P < 0.001$ for exotic annual grass and perennial grass, respectively; not shown). However, the total area/pasture needing to be sampled in the 531-m^2 plots to meet TSR was ~1 000 times larger than the total area monitored in 1-m^2 plots to achieve the same threshold (Fig. 2). TSR was similar between

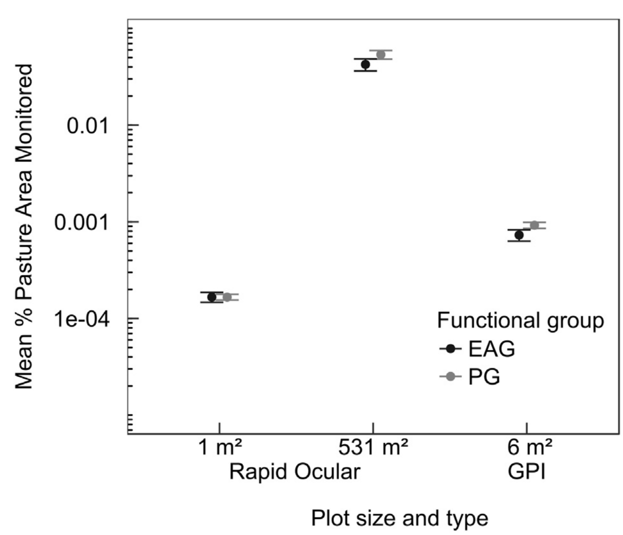

Figure 2. Mean total percent of pasture area or number of plot samples needed for exotic annual grasses (EAG) or perennial grasses (PG) to attain TSR, the threshold sample requirement determined as 0.2 SE/mean, for the different plot sizes and sampling types (rapid ocular or grid-point intercept, GPI). n = 18 pastures for EAG and 38 for PG (all pastures and cover types that met TSR for all three plot sizes).

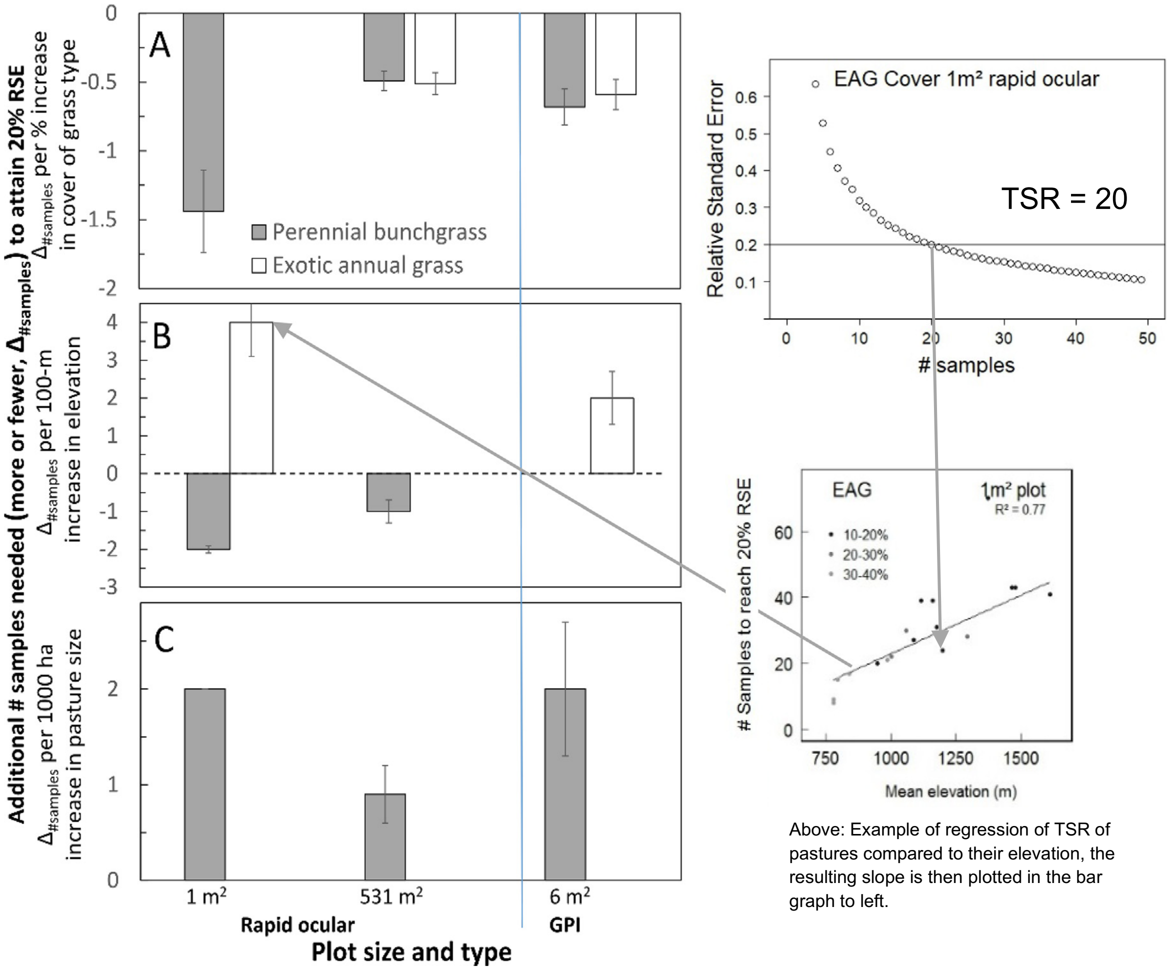

Figure 3. Slopes of the relationships between TSR (threshold sampling requirement, = number of plots needed to attain SE/mean ≤ 0.2) for perennial or exotic annual grasses (EAG) in the different plot size and sampling types to their dominance of **(A)** community cover, **(B)** elevation, and **(C)** pasture size. Regressions show an example of how the data are derived from plots within a pasture (upper right graph) to the slope of TSR and landscape variables across many pastures (lower right graph). See Table 3 for the statistical coefficients and significance for each model.

the rapid ocular and grid-point intercept methods for exotic annual grass ($P = 0.12$), but more plots were required for grid-point intercept than the 531-m^2 rapid ocular estimate plot for perennial grass (+9 plots/pasture, $P < 0.001$; not shown).

Landscape Variable Effects

TSR was not significantly related to the number or spatial diversity of soil types, drill seeding heterogeneity, or any metric of precipitation and heat load within pastures. TSR increased with pasture size for perennial grass (1–2 plots/1 000 ha), but not for exotic annual grass, in rapid-ocular plots (Figs. 3B and C; Table 3). TSR increased with elevation by 4 plots/100 m for exotic annual grass in 1-m^2 plots, but decreased with elevation by 1 plot/100 m in 1-m^2 plots and by 2 plots/100 m in 531-m^2 plots for perennial grass. Furthermore, TSR increased for both exotic annual and perennial grass by 0.5 to 1.5 plots per 1% decrease in their respective cover, except for exotic annual grass in 1-m^2 plots. TSR was more sensitive to landscape variables in the 1-m^2 compared with 531-m^2 rapid-ocular plots (see effect sizes in Figs. 3A and B).

TSR for perennial grass measured with grid-point intercept increased with variation in elevation (+6 plots/100 m change in standard deviation of elevation, Table 3), while TSR for exotic annual grasses measured with grid-point intercept was correlated with mean elevation (+2 plots/100 m increase in mean elevation, Table 3). Variability in TSR as a function of the landscape variables could be predicted better for data from the grid-point intercept compared with the rapid-ocular method (for exotic annual grass: $R^2 = 0.83$ with grid-point intercept, $R^2 = 0.68$–0.77 with rapid ocular; for perennial grass: $R^2 = 0.73$ with grid-point intercept, $R^2 = 0.62$–0.65 with rapid ocular, Table 3).

Discussion

In this study, we identified how several sources of spatial heterogeneity affect sampling effort needed to attain a statistically defensible threshold of 0.2 RSE within pasture units. This technique can be used to design an initial monitoring plan for permanent plots that can continue to be tracked over time. In agreement with Pechanec and Stewart's (1941) experimental assessment of the tradeoff in number and size of plots used (theirs was for biomass of two forbs), we found TSR was attainable with less area searched using smaller plot sizes (1 and 6 compared with 531 m^2), in spite of less variation among the larger plots. The increases in TSR with larger pasture sizes, topographic variation, and scarcity of the measured vegetation type are also reasonable (Figs. 2 and 3), as these factors provide more opportunity for variation. The weaker effects of these factors on TSR for large plots (531 m^2) compared with 1- or 6-m^2 plot sizes likely relate to greater variability being captured within the larger plots than in the smaller plots.

Greater sampling requirements for estimation of exotic annual cover at higher elevation pastures, and conversely greater sampling effort for estimation of perennial grass cover at lower elevations (Fig. 3, middle)

Table 2
Confidence interval (CI) equivalence to 0.2 relative standard error (RSE) for various mean percent cover values, based on z-scores. The RSE calculations made can be related to 95% confidence intervals for a given mean cover value (μ) using the following equation: 1.96 times 0.2μ.

Mean % cover	95% CI	80% CI
5	± 1.96	± 1.28
10	± 3.92	± 2.56
15	± 5.88	± 3.84
20	± 7.84	± 5.12
25	± 9.80	± 6.40
30	± 11.76	± 7.68
50	± 19.60	± 12.80
70	± 27.44	± 17.92

may relate to their opposing dominance along this elevational gradient. Cheatgrass is scarcer and thus has a patchier distribution at high elevations compared with low elevations, whereas perennial grasses have the opposite pattern (Chambers et al., 2014). We additionally identified a tradeoff in plot-size choice as plant dominance changed. For example, at low cover of perennial grass, a 10% decrease in cover led to needing +14 more plots per pasture if using 1-m^2 plots, compared with only 5 additional plots if using the 531-m^2 plot size.

TSR was more accurately predicted for grid-point intercept plots than ocular estimate plots, given known variation in landscape variables, supporting Booth et al.'s (2006) contention that the grid-point intercept method minimizes observer bias compared with less-guided "ocular" estimates. We found this to be true in our calibration of plots, since the rapid ocular estimates tend to vary more among observers, particularly in the mid-range of cover values (i.e., better concordance at high or low cover values). Excluding travel time, the grid-point intercept photo and the 1-m^2 rapid ocular estimate take approximately 1 minute each to do in the field, whereas the 531-m^2 rapid ocular estimate takes approximately 5 minutes. Whereas acquiring the aerial photograph for the grid-point intercept method requires little time in the field, at least 5 minutes per photograph is required for manually estimating the vegetation cover within it using SamplePoint (Pilliod and Arkle, 2013). By comparison, the line-point estimate (LPI) approach typically requires a minimum of 30 minutes to measure the same number of points in grass-dominated areas, and can easily require 2 to 3 times as long with high cover or adverse conditions (e.g., wind). Including processing of grid-point intercept photographs, Pilliod and Arkle (2013) estimate that a single standard AIM plot with three 50-m LPI transects is equivalent to about 20 to 25 grid-point intercept quadrats in terms of person-hours, and moreover the methods resulted in similar plant cover estimates (Pilliod and Arkle, 2013).

Our approach differs from the BLM AIM program because AIM is focused on assessing temporal trends at a small number of sites; whereas the need and goal for our monitoring was a relatively rapid assessment of vegetation cover over a large heterogeneous area to provide timely information for annual decisions (i.e., adaptive management). In the context of initial response to megafires, the decisions can include if, where, or when seedings, herbicide spraying, or grazing deferment should occur as vegetation recovery patterns are observed in the first few years after fire. The time requirements for line-point intercept detract from its suitability for rapid and spatially extensive assessment of plant cover, and thus fulfilling these management needs. However, after the initial site stabilization and fire recovery, it becomes more important to assess vegetation temporal trends. Trends can be subtle and often will require a type of monitoring which provides a high level of detail and spatial coverage of a single plot, such as is accomplished with LPI in AIM monitoring. Furthermore, AIM data collected prior to fires could greatly help guide the process of determining sampling effort, such as the process described here. Selection of monitoring strategy is more effectively made if objectives for it are considered concisely. Our monitoring template fulfills a different monitoring need than AIM, although both could be used within the same management area as objectives shift over time.

We chose an RSE of 0.2 for our analyses, but for some management situations, use of RSE > 0.2 (e.g., RSE ≥ 0.3) may be acceptable (Table 2). If the cover of a functional group(s) being monitored is sparse, the costs of achieving a RSE of ≤ 0.2 are likely to be relatively high. This is important to consider for any monitoring effort.

Implications

One sample size clearly cannot fit all pasture sampling needs, and so customizing the plot sampling method, size, and density will greatly improve monitoring effectiveness. The regression models we provide could be used as first approximations of sampling requirements for a given confidence level on landscapes similar to those of the Soda Fire. Having some crude preliminary estimate of vegetation composition along with readily available landscape data (e.g., elevation) will allow a priori estimation of the confidence level for a given sampling effort. Although quantifying vegetation in fewer large plots appeared less efficient, they may become a more efficient option where access is limited (i.e., where the cost or logistics of visiting larger numbers of plots is problematic). Furthermore, this analysis shows that sampling effort could be minimized by stratifying monitoring based on landscape variables and then sampling within strata, but we recognize that decision-making often occurs at jurisdictional levels requiring monitoring that spans gradients in landform, topography, and plant communities.

Table 3
Multiple linear regression results for models of variables affecting threshold sampling requirement (TSR) of exotic-annual and perennial grass cover.

Plot size, sampling type	Plant cover type	R^2	Coefficient	Estimate	t	P
1-m^2 plot, rapid ocular	Exotic annual grass	0.77	Slope range (°)	0.48 ± 0.2	2.8	0.01
			Mean elevation (m)	0.04 ± 0.009	4.11	0.0009
	Perennial grass	0.65	Mean PG cover	−1.44 ± 0.3	−5.03	<0.001
			Pasture size (ha)	0.002 ± 0.000	3.6	<0.001
			Mean elevation (m)	−0.02 ± 0.001	0.02	0.001
531-m^2 plot, rapid ocular	Exotic annual grass	0.68	Mean EAG cover	−0.51 ± 0.08	−6.19	<0.000
			Herbicide index	29.8 ± 8.7	3.5	0.001
	Perennial grass	0.62	Mean PG cover	−0.49 ± 0.07	−6.82	<0.001
			Pasture size (ha)	0.0009 ± 0.0003	2.91	0.005
			Mean elevation (m)	−0.01 ± 0.003	−4.11	<0.001
6-m^2 plot, grid-point intercept	Exotic annual grass	0.83	Mean EAG cover	−0.59 ± 0.11	−5.46	<0.001
			Mean elevation (m)	0.02 ± 0.007	2.83	0.009
	Perennial grass	0.73	Mean PG cover	−0.68 ± 0.13	−5.20	<0.001
			Pasture size (ha)	0.002 ± 0.0007	3.60	<0.001
			SD of elevation (m)	0.06 ± 0.02	2.29	0.03

SD indicates standard deviation; grid-point intercept; PG, perennial grass; EAG, exotic annual grass.

Please cite this article as: Applestein, C., et al., Appropriate Sample Sizes for Monitoring Burned Pastures in Sagebrush Steppe: How Many Plots are Enough, and Can One Size Fit All?, Rangeland Ecology & Management (2018), https://doi.org/10.1016/j.rama.2018.05.003

Our analyses indicate that these landscape variables affect required sampling effort and should be considered in sampling design.

Acknowledgments

Cindy Fritz and the Soda Fire response staff of the BLM, Martha Brabec and Justin Welty of the USGS, and the USGS and Great Basin Institute Soda Monitoring Crew assisted with logistics and sampling. Gordon Toevs of the BLM provided helpful comments.

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